Second, there are additional statistical challenges to these tests. DerSimonian and Laird's [8] Q statistic is specific to random effects models, while Cochran's Q statistic [7] is not presented in the context of covariates: their original derivation is only for models that do not control for confounding. This is presumably because the authors are well aware that one cannot directly compare magnitudes of odds ratios from separate analyses, a point only recently highlighted in the applied literature [11–13]. In addition, because of differences in the weighting of trials when calculating Cochran's Q for different summary statistics, these comparisons may not be particularly meaningful and may be misleading [10].

Third, in practice estimating a model with a rich specification of covariates can provide a good approximation to other models. We showed this in another article in which multivariate logistic regression could recover the adjusted risk ratio even when the data generating process is an odds ratio [14]. DerSimonian and Laird [8] also argue that although choosing the wrong measure could imply heterogeneity in treatment effects, in practice this would not tend to happen unless the rate for the control group varied widely or was close to either zero or one.

Fourth, our preferred approach to choosing a measure is to begin with the policy or research question. Even if this approach requires tolerating reduced precision because of heterogeneity, we hold with Tukey [15], "Far better an approximate answer to the *right* question, which is often vague, than an *exact* answer to the wrong question, which can always be made precise." We consider the statistics to serve the substance and not vice versa.

We thank Valkenhoef and Ades for their careful read of our article, and for drawing attention to important issues about conducting meta-analyses. Their letter is a great reminder that assumptions matter, that some statistical models are theoretically incompatible with seemingly similar models, and that getting the right statistical model is extremely important. We hope that this exchange will generate better understanding of the strengths and weaknesses of different approaches to indirect comparison meta-analyses.

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ERRATUM

In *Value in Health* Volume 16, Issue 1, pages 46-56, (January/February 2013), the correct authors listing for the following article should be as follows:

Cost-Effectiveness of Gene-Expression Profiling For Tumor-Site Origin

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